Combining Reality Capture Technologies for Construction Defect Detection: A Case Study

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Abstract: Defects that occur during the construction process account for a large percentage of overall defects in the built environment. Defects waste time and money, and affect the overall performance of the built environment. These problems can be minimized with proactive application of advanced scanners, sensing, and data modelling techniques. Researchers in the departments of Architecture, Robotics, and Civil and Environmental Engineering at Carnegie Mellon University are investigating ways to integrate suites of emerging evaluation technologies to help find, record, manage, and limit the impact of construction defects. As part of this effort, the researchers have conducted a case study on a construction site near Pittsburgh, Pennsylvania. The case study serves to identify challenges in applying specific reality capture technologies and in coordinating suites of these tools on construction sites. The researchers conducted the following activities: creation of a 3D design model, generation of strategies and mechanisms to create 3D as-built models; establishment of specific measurement goals; creation of laser scanner and sensor planning software; targeted use of laser scanners and wireless embedded sensing for capturing as-built data; and analysis of captured data for possible defects. This paper discusses the process of deploying sensing and scanning tools on the case study construction site, and the process of implementing components of an integrated early defect detection system.

Keywords: laser scanning, embedded sensing, 3D modelling, defect detection

1 Introduction

A large percentage of defects in construction occur during the construction process, resulting in costly rework and adversely affecting the overall performance of the built environment [BF 87]. New technologies are emerging that allow faster, easier, and more thorough collection of site information, and thus have the potential to help identify defects during construction. For example, laser scans can quickly create 3D models of the built environment. One can make measurements within these models and compare them to the measurements taken from the design to identify defects [CYR 99]. Also, sensors can be embedded in the built environment to monitor the performance of components and materials, and to compare those measurements to performance specifications for defect detection [SAC 99].

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Researchers from the Architecture, Robotics, and Civil and Environmental Engineering departments at Carnegie Mellon University are exploring the utilization of advanced scanning, sensing, and data modelling techniques for identifying defects early in the construction process [AKI et al. 02]. The team uses laser scanners and embedded sensors to assemble as-built information into a digital model. This model is then compared with a digital design model in order to detect unacceptable deviations from the properties specified in the design specification. As part of this effort, we conducted a case study on a construction project near Pittsburgh, Pennsylvania to identify challenges in applying specific reality capture technologies and in coordinating suites of these tools on construction sites. During the case study, we embedded sensing in concrete and frequently obtained laser scans. This paper discusses the case study experience and provides insight into potential benefits and challenges of the envisioned integrated early defect detection system.

2 Detailed Description of Case

Construction started in June 2002 on an approximately 50,000 square foot office and production facility for a pre-cast concrete manufacturer. The design was communicated in a collection of specifications, 2D architectural drawings, and manufacturer drawings. The schedule comprised approximately 130 activities over a span of eight months. The case study commenced with the beginning of actual construction, and continued throughout the remainder of the construction process. We visited the case study site regularly throughout the eight months, and collected data about the as-built conditions by embedding sensing and conducting laser scans. Research continued both indoors and outdoors, in different seasons, and at different times of day, to account for a full range of possible operating conditions. We chose this project because of its schedule and location, and because of the permission granted to embed sensing and to conduct laser scanning sessions throughout the course of the project. Additionally, the project we chose is a manufactured building, and is therefore less subject to design errors. Hence any discrepancies discovered during the case study are more likely to be due to construction errors. In order to focus the case study, we chose to specifically target only the A and B grid lines across the length of the production facility as shown in Fig. 1. This region comprises a large number and variety of components and corresponding construction methods, and a range of environmental conditions to effectively assess the technologies used.

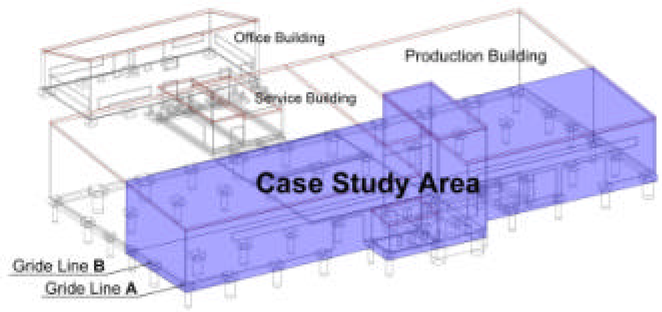

Figure 1. The shaded area indicates the focus area (grid lines A and B)

3 Approach

3.1 Overall Approach

Using available design documentation, we modelled the facility, determined measurement goals attainable by available sensing and scanning equipment, and planned embedded sensor and scanner locations and data collection times. The sections below describe the details of the approach and state the lessons learned based on the implementation of the approach at the case study site.

3.2 Three Dimensional Design Modelling

The process of comparing as-built to as-designed conditions requires that the design model be represented at a comparable level of detail to features that are extracted from the reality capture technologies. For comparison with the geometric features derived from laser scans, the design model must be in 3D, and highly detailed. For comparison with non-geometric features, the components must be represented with expected performance attributes that correspond to the gathered data.

We chose Graphisoft ArchiCAD 7.0 as an environment to model the design in sufficient detail based on available sources of design definition. We used the environment not only for 3D modelling, but also to store non-geometric attributes such as material-related information. Moreover, we chose ArchiCAD for its ability to generate IFC 2X-compliant code for information exchange between the design software and the early defect detection software that will be developed in this research. It also provides GDL (Geometric Description Language), which permits modelling of customized objects, such as pre-fabricated steel members.

Often, building construction does not start with a complete design. The level of completion of construction documents depends on the project delivery method. The case study project, for example, was a negotiated contract that started with 90% complete design documents (issued April 2002), to which the research team was given access. Later in the construction progress, the revised set of construction documents (issued July 2002) and the manufacturer's pre-fabricated steel installation drawings were made available to the research team, providing greater definition to the 3D model. We found that not all design details for pre-fabricated components were translated to building design documents. Some complex components, such as a pre-fabricated cement silo, were installed in relatively few sub-assemblies, and hence were not reflected in detailed construction documents. Incomplete contract definition and documentation challenged our ability to model existing designs in 3D in sufficient detail to compare to as-built conditions.

Based on the modelling experience, we concluded that the generation of 3D design models needs a supporting framework based on as-built conditions as well as incremental design modifications, manufacturers' geometric information, and the construction process model. Additionally, the model required of this approach must have a flexible representation to accommodate different levels of detail and uses over time, such as the low-detail view needed for scan planning and highly detailed view for geometric comparison of objects.

3.3 Determining Measurement Goals

We reviewed available design documentation for requirements to be verified using laser scanners and embedded sensing at specific points in the construction schedule. These are referred to as the measurement goals. For example, the team was interested in the requirement in the specifications that columns be plumb when installed. We first determined which columns had been built by the next planned scanning date, and for these objects determined specific measurements needed in order to confirm the requirements. In the case of column alignment, the measurement goals were a set of points along the length of the column and along the slab at the time of scanning. With the resulting scan data, we can compare the as-built data collected on the points of interest to each other, and to the as-designed column model in order to confirm that the column is properly aligned.

3.4 Embedded Sensing and Sensor Planning

Embedding sensors into a facility requires commitment to a certain location and time period for sensing, without the option to revisit the sensors for maintenance or replacement. There are many attributes to consider in an embedded sensor plan, for example: modality, location, time and duration of sensing, and data communication and storage. It may be possible to consider all these in a small deployment of sensors at a single point in time; however, sensor planning becomes much more difficult for larger deployments under the dynamic and complex conditions experienced on construction sites over time. Hence formalizing and automating embedded sensor planning is important prior to placing these sensors.

Given a construction schedule, design model, and defined measurement goals, the output of the embedded sensor planning process is a series of decisions of when and where to sense what properties of a component for how long and with what sensor. To simplify this process for the case study, we used a single type of sensor and fixed a receiver and data logger in a secure construction trailer. We chose sensors and receivers provided by Microstrain to sense and communicate temperature data wirelessly. We chose to employ the concrete maturity method to ascertain the strength of concrete based on its temperature while curing [GER 01]. In parallel with the field deployment, we tested the same material and sensing system in a lab.

Based on the success of the lab results, we found that the initial formalism developed can correctly choose a sensing approach to satisfy a given measurement goal. Also in lab tests, we confirmed that the concrete maturity method can be applied with embedded thermocouples to determine the eventual strength of concrete. We discovered that the data logger needed additional memory in order to make sufficient temperature readings in the field, where the timing of concrete placement is more variable than under controlled conditions. In order to make meaningful deployments of sensing within the bounds of sensor infrastructure capabilities, crews need more than simple decision-making assistance, since even a small deployment has intricate considerations with respect to the built environment.

3.5 Laser Scanner Planning

The goal of laser scanner planning is to optimise the use of scanners to achieve a given set of measurement goals in the built environment. Total saturation of the construction environment with laser scans is clearly an inefficient option since not all areas require constant or frequent inspections. At the same time, sparse scanning risks missing areas of interest that may be occluded or otherwise hard to access for necessary measurements. To minimize the cost of scanning, researchers from the Robotics Institute constructed an algorithm that determines optimal scanner configurations based on current site conditions, measurement goals, and the goal of minimizing costs. Since no pre-existing algorithm for this goal was available, the researchers built it for this purpose.

First, the system generates the space of potential scanner placements for a set of measurement goals. It then selects a minimal set of subspaces to take advantage of views that can achieve multiple goals simultaneously. Finally, it selects scanner locations and generates a path to minimize the transit cost between locations. The application assumes that the scanner scans in a 360° field of view from its position. Thus, the scanner configuration space is a line-of-sight, bounded 2D region around a measurement goal that encompasses all the points within scanning range of the scanner. A simulated annealing algorithm is used to determine the order in which to visit the configuration spaces. The order is ranked by path length between configuration spaces. More details can be found at [LAT et al. 02].

The algorithm performed well on the case study site with few overlapping goal spaces, but had difficulty when multiple goals existed in close proximity. Ultimately the lessons learned by applying this approach to the case study site, coupled with theory to determine the net-present-value of scanner placements, will lead to a system that will be more cost efficient than naïve scanner saturation.

3.6 Laser Scanning Process

Given laser scan plans, we experimented with two available laser scanners, one a commercially-available Zoller + Fröhlich LARA 25200 (Z+F scanner), and the other, a research test-bed, composed of two actuated SICK lasers (CTA scanner). Both generate 3D point clouds as their output.

The Z+F scanner is able to scan 360° horizontally and 70° vertically, and capture range and reflectance data for each point. It has a maximum range of 25 meters. It takes approximately 90 seconds to complete a scan; with spin-up time and interface navigation included, we averaged 6 minutes per scan. An example of a Z+F scan on the case study site follows in Fig. 2.

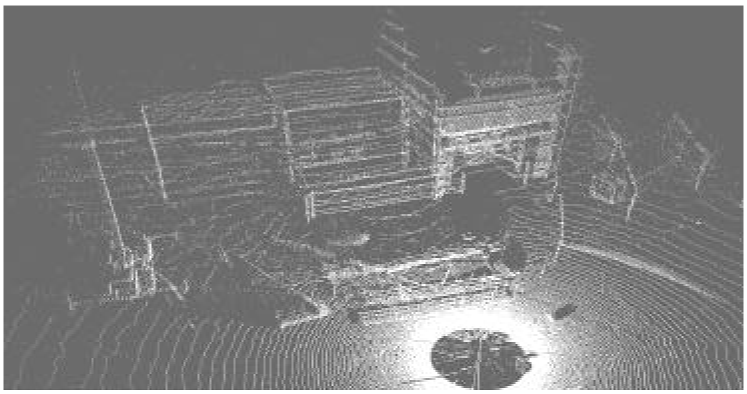

Figure 2. Z+F scanner output

The CTA scanner is a test-bed made from two SICK lasers: one mounted horizontally and one vertically, with each able to scan a 180° line. The CTA scanner has a maximum range of 80 meters. A scan takes approximately 45 seconds to complete; total scan time, including spin-up time and interface navigation, averages 2 minutes.

The scale and detail required for each measurement goal determines the choice of scanner. Data generated from the Z+F was of very high density and quality, with one problem: range data that exceeds 25 meters wraps around to 2 meters, causing overlap of far data with near. When scanning inside buildings with flat features (such as ceilings), this can be corrected with a vertical line algorithm, but columns at varying distances disrupt this correction. The SICK lasers do not have this problem.

We found that the ability to scan up to 80 meters can make construction applications of laser scanning time-effective, especially for a large number of measurement goals. In addition to the scan and transit times, set-up time between scans, including establishment of ground truth with a theodolite, is about 5 minutes. Initial set-up time for both scanners is straightforward at about 20 minutes to unload, assemble, and check all systems. Both scanners can achieve multiple measurement goals with a single scan. However, we found that the quality of the scans generated is highly dependent on the sensor plan.

We discovered a number of challenges in this application of laser scanners. Our set-up mounted each scanner on top of a cart with the rest of the computer equipment stored underneath, making it difficult to move over rocks and mud. The equipment was therefore not sufficiently mobile or ruggedized for the full range of construction site conditions. The need for power mandated that we bring generators to power the equipment if power was not available on site. Lastly, the scanning process was at times conducted during the working day, and the team was careful to avoid scanning near workers. Although the lasers used are eye-safe, the team was careful to avoid interrupting or distracting the construction process.

3.7 Object Recognition

Using the 3D point cloud output of the laser scanning process, the team was able to visualize the geometric as-built site conditions. However, a point cloud is computationally too cumbersome a representation to allow high-level reasoning about defects and their early detection. Object recognition provides the bridge between the raw data and a CAD model of the site, abstracting the point cloud data into a higher-level, more portable representation.

Researchers from the Robotics Institute are developing an object recognition system and adapting it for construction applications. The system determines the position and orientation (pose) of free-form 3D objects within a 3D data set such as a point cloud or a surface mesh. The algorithm recognizes objects based on shape using a localized measure of surface shape to identify similarly shaped regions between the object model and the 3D scene. Details of the algorithm can be found in [JH 99].

For this case study, the team identified several types of objects to test the object recognition system, including steel columns, x-bracings, and concrete piers (Fig. 3). Although the object recognition system can detect objects with arbitrary and unknown pose, the existing site model provides an initial estimate of the location of the model objects within the 3D point cloud. This *a priori* knowledge allowed us to focus the recognition algorithm on the relevant region of the data and to process the data at a higher resolution than would be possible if the entire point cloud was used. Fig. 3 shows an example of the recognition progress for a steel column.

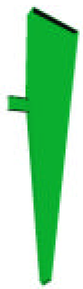

Fig. 3.1 Design Model (Step 1)

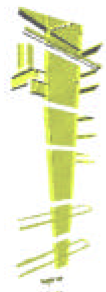

Fig. 3.2 Range Data from Laser Scan (Step 2)

Fig. 3.3 Column Recognized Using Information from Steps 1 and 2

In choosing the test objects for recognition, the team found that often the easiest objects for the system to recognize are the hardest objects to model with a CAD system. In many cases, the CAD models for the more complex objects, such as the cement silo, were not easily available. Going forward, the object recognition team plans to extend our recognition algorithms to directly model the constraints implied by the known approximate location of the target object and to handle parameterized object models (such as girders of varying length). These extensions will permit recognition of a larger proportion of the objects from the CAD model.

3.8 Reasoning about Specifications

After converting the 3D design model and the 3D as-built model into VRML, the team plans to overlay the models to look for discrepancies, and compare them with the allowable discrepancies described in the specifications. This visual inspection will allow us to visualize discrepancies from different angles, providing a much more detailed comparison than on-site during data collection. Additionally, we envision automating the process of comparing as-built and design models.

We encountered data exchange challenges while assembling the data for comparison with design specifications. The design information, the data from the laser scanners, and the data from the embedded sensors need to be in the same format to allow for comparison. For the comparison of the geometric design and as-built information, we agreed to use VRML as a preliminary data format. However, since other information, e.g. from embedded sensors, needs to be included in the models, another data format is needed.

Another problem was related to the resolution of the laser scanner. Poor resolution sometimes made the comparison of the scanned as-built model with the design model difficult. In some scans, we tried to assess the x-bracings between two steel columns. It was possible to compare the design model with the raw data from the laser scan and to see if any discrepancies existed. However, once the noise-reduction algorithm processed the raw scanning data to remove unwanted noise from the data, the x-bracings were also removed from the data. This was because the resolution in which the x-bracings were shown in the raw data was too low; the algorithm categorized them as noise. We found that a sensitive noise-reduction algorithm that would eliminate only the real noise from the original raw data is needed to not eliminate critical information. However, the comparison of the raw scanned data with the design model can easily be done manually and allows more thorough site inspection. This is possible because the information can be collected quickly and accurately and the user can adjust the view on the virtual representation of the data, allowing for better and more detailed inspection results.

We found that even most detailed design specification provided was incomplete. In particular, allowable deviations were not always specified. Also, the team found contradicting specifications, making reasoning about them impossible without clarifications from the project manager.

3.9 Conclusions

Through this case study, we identified a broad range of considerations associated with employing suites of reality capture technologies for early defect detection on construction sites. These are both organizational and technical.

At the organizational level, good collaboration between the project participants and the evaluation crews is critical. Laser scans and sensor embedment needed approval by the owner and the contractors. At the site level, crews in charge of scanning and sensing were careful to not interrupt the construction process. Lastly, architects, fabricators, and contractors had to be willing to provide the information and specifications needed at the right amount of detail. In this case study, we had to create digital 3D design models from the paper-based information received, which is a tedious and time-consuming task. This process could have been facilitated considerably by having the design available digitally.

The modelling experience showed the need for a framework to support the generation of 3D models based on as-built conditions as well as incremental design modifications, manufacturers' geometric information, and the construction process model. The models needed for this defect detection approach must have a flexible representation to accommodate different levels of detail and uses over time.

While lab results verified that our sensing and scanning approaches work in theory, we encountered technical issues with the equipment used. The data logger for the embedded sensors used required additional memory to provide conclusive results. Since the range and resolution of the scanners can affect the usability of the acquired data, careful and preferably automated scan planning is mandatory. The current scan planning approach has to be improved to allow scan planning in 3D environments as well as incorporating more advanced expense metrics and accommodating multiple measurement goals. Ideally, algorithms that remove the noise from the scanned data need to be less likely to erase real data. This can be aided with *a priori* information about the scanned environment.

Furthermore, safety is an issue, both for the equipment and the personnel on site. The laser scanner set-up used was not completely rugged enough for all site conditions. Hence equipment safety is a concern, especially during construction operations. The embedded sensing installed was sufficiently ruggedized, although the wireless receiver was placed inside a construction trailer for protection from theft and the environment. The use of lasers on active construction sites raises the issue of whether the equipment is eye-safe, which is confirmed by scanner manufacturers, although eye contact is preferably avoided.

Due to the significant amount of information that can be quickly collected on site with the discussed approach and due to the high accuracy that the collection technologies used provide, the research team comes to the conclusion that this approach is worthy of further pursuit and refinement. Improvements need to be made in the areas of equipment ruggedness and mobility, data processing algorithms, information exchange, and sensor and scan planning. We are also employing the lessons learned from the case study to understand the requirements for automated defect detection using reality capture technologies and advanced data modelling techniques.

4 Acknowledgements

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